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TECHNICAL REPORT



ACTIVE PARTICIPATION  
IN HIGHLY AUTOMATED SYSTEMS:  
TURNING THE WRONG STUFF INTO THE RIGHT STUFF

Jacqueline R. Idaszak and Charles L. Hulin

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# Abstract

A failure of human operators to take an active monitoring role in complex automated systems has resulted in operators who are less able to improve the efficiency and stability of a system and unable to make a transition from normal scanning behavior to the detection, diagnosis, and correction of system failures. Passive monitoring is common when operator training follows an associative or stimulus-response model. In this study, we manipulated operator-system participation and operator-operator communication to investigate the effects of increases in active participation on operator monitoring and problem-solving performance. 112 subjects worked as operators of a simulated process system. Operators worked in teams of two on both a monitoring task and, after the system failed, a diagnostic task. The results of this study suggest that active participation in the system improves both monitoring and diagnostic performance. In addition, active participation reduces boredom during monitoring, and stress while diagnosing a failure. Communication, on the other hand, was found to be a mixed blessing. Communication tended to facilitate performance of active participants, but degraded performance of passive participants. The implications of these results for system design, operator training, and future communication studies are discussed.

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Active Participation in Highly Automated Systems:  
Turning the Wrong Stuff into the Right Stuff

The role of crew members of many automated systems has changed greatly in recent years due to the continual enhancement of automation. By automating system control and shifting control responsibilities to computers, the human's role is now supervisory in nature (Sheridan & Johonnsen, 1976). The supervisory role of crew members requires cognitive skills such as inquiry, reasoning, integration, and pattern matching; social skills including communication and coordination; and problem-solving skills, rather than psychomotor skills (Morris & Rouse, 1985). Current research in cognitive and aviation psychology seems to suggest that the information processing and social interaction requirements of human operators have been largely neglected (Brecke, 1981; Montague, 1986; Weiner, 1985; Weiner & Curry, 1980).

Training programs for crew members of aircrafts, for example, are often designed in accordance with a stimulus-response pairing of signals from the aircraft and reaction type motor responses from the pilot (Braune & Trollip, 1981). A great deal of effort in aviation training is spent teaching pilots an abundance of rules and procedures, and training them to use the appropriate procedures and actions in a given task. Comparatively little time is spent on learning information processing skills (Braune & Trollip, 1981), judgment skills (Brecke, 1981); or communication skills (Foushee, 1981; Foushee & Manos, 1981) essential for handling nonprocedural tasks and emergencies.

Pilots are not unique in their task indoctrination. In a recent review of a report published by the Office of Technological Assessment (OTA), Schuck (1985) concluded that typical instructional programs in automated work places are reactive. She describes traditional training procedures as highly structured and task specific where trainees learn only enough to control their subsystems. The programs were criticized for focussing on discrete tasks and skills, thus giving operators little opportunity to develop intellectual skills or acquire a complete understanding of the process. In her report, one worker was quoted as saying, "I know what buttons to push if things get out of whack, but I really don't know why it happened," (Schuck, 1985, p. 68). As a consequence of this type of reactive indoctrination, a generation of passive and

apathetic operators now work in complex automated systems--unwilling to take responsibility for their system and unable to deal with unplanned changes or emergencies (Boddy & Buchanan, 1986). It appears that a new, more active conceptualization of the operators' supervisory role is long overdue. The study presented in this paper investigates variables that may help reduce the passiveness in operator behavior.

Two issues are at the center of our inquiry. One of these is the study of operator participation while controlling outer-loop variables. Outer-loop variables provide setpoints or goals for a system and allow the automated control process to handle internal adjustments and feedback loops; the computers and machines provide inner-loop control. Given this type of automated system, operators must actively pursue information while outside-of-the-loop to prevent any deterioration in their level of familiarity with the system (Wickens, 1984). Furthermore, if operators fail to participate actively in information gathering, processing, and exchange, they will be less able to deal with unexpected changes and problems.

A second issue concerns the social consequences of technological development in the work place. The enhancement of automated components in complex automated systems increases the amount of information operators have to process and use to control the system. Many complex systems require more than one operator to monitor and adjust system variables. Therefore, in order for operators to be familiar with the state of the system, they must share information and coordinate their actions.

Together the research done in these areas has focussed on the operators supervisory role and the effects of active operator-machine interfacing and operator-operator communication on crew performance in highly automated work places. Both the information obtained from other operators through communication and the information obtained from the system are important to successful system control. Yet, little research has examined these two issues together. In the present study, the effects of active task participation and operator communication will be investigated at all phases of an operator's new role--monitoring and adjusting; detection; and system failure diagnosis.

### Problem Definition and Theoretical Framework

The problem we are investigating can be stated in the form of a question. How does increased automation affect the demand for active operator-machine and operator-operator interactions? In other words, we are interested in studying if successful control and problem-solving performance could be achieved by having operators interact with each other while actively participating in system operations.

Our theoretical framework is based, in part, on that of Rasmussen (1983). According to Rasmussen, operators have a goal state that they would like to achieve, and human activity is influenced by this goal. In a steady system state, actions or rules that have proven successful in the past, may be used to achieve a desired goal. Two levels of behaviors are common in these circumstances (See Rasmussen, 1983, for a more complete description). At a skill-based level, operators perform highly automatic, sensory motor actions without conscious control. Alternatively, an operator may use available heuristics, procedures, or rules and perform at a rule-based level.

There are times, however, when available rules are not appropriate. In these situations operators rely on their knowledge of the properties, dynamics, and current state of the system (internal representation) to select a sequence of behaviors that will help them achieve their goal. This level of behavior has been categorized as knowledge-based.

Rasmussen categorized these behaviors according to constraints in a deterministic environment. Our theory is based on a rejection of this deterministic view. Rather it is proposed that the level of behavior operators use is based on the amount of influence operators are given -- through training, design, or management -- to reach a desired goal. Further, the level of behavior crew members choose will closely parallel the degree of active operator participation allowable in a system and will also influence the type of inter-operator communication possible. If rule-based behavior is chosen, operators simply follow rules or passively wait for signals from the system and apply the appropriate procedures. Inter-operator communication is characterized by the reading of system signals and appropriate procedures. At the knowledge based level, much more active participation is necessary even in a normally operating system state. Operators plan ahead, consider goals and appropriate setpoints.

and determine how to improve system efficiency or productivity. Communication in this case is characterized by the timely exchange of information, questions, concerns and ideas that help crews achieve their goals. Thus, active operator-system participation and inter-operator communication appear to be variables that will help improve operator control and problem-solving performance.

#### Active Participation

Researchers studying operator behavior in complex automated systems have traditionally described operators as active only in emergency situations. Wickens (1984), for example, wrote:

"The process control operator's task has typically been described as hours of intolerable boredom punctuated by a few minutes of pure hell." (pp. 467)

Also, in Rasmussen's (1983) behavior typology, he only recognizes a knowledge-based behavior level when problems or unplanned changes arise. This is not to say that automating a process is necessarily bad. In fact, Fuld, Liu, and Wickens (1987) found that operator error detection may be better when a process is in an automatic mode compared to a manual mode. Rather the issue is the extent to which an operator should participate actively in an automated process. Active human-system participation must begin while the system is normal in order to acquire the problem-solving, judgment, integrating, and communication skills operators need to handle unexpected changes.

The practice of active human-machine interaction is most popular in the training and education literature. According to Schuck (1985), active task participation begins at training. Through instruction, students can extend their boundaries by sharing information to increase each others knowledge of the system. Training and work environments, therefore, must be conducive to inquiry and the development of ideas and solutions. Rather than simply memorizing preorganized material about the system (rule-based level of behavior), workers should be encouraged to pose problems; generate hypotheses, questions, and information; and problem-solve (knowledge-based level of behavior).

Carroll, Mack, Lewis, Grischkowsky, and Robertson (1985) provide evidence that operator-machine participation improves operator and system performance. In their study an instructional program for word processors was constructed that was intended to produce a work environment conducive to exploration. The

results of their study show that, when learning a word processing system, active interfacing (self-initiated behavior, self-set goals, exploration) resulted in faster error recognition and recovery time and less time to transfer the skills from training to a post test than traditional procedure-based training.

Anecdotal evidence also exists to support active involvement by humans in complex automated systems (Buchanan & Boddy, 1983). Buchanan and Boddy, for example, told of several behaviors of ovenmen at a biscuit making plant. New technology provided the ovenmen with direct and rapid feedback on the current state of production. Rather than simply monitoring system variables and then removing the product, the ovenmen used this information to make adjustments to oven temperatures and other variables and change the characteristics of the biscuits. Production improved and the ovenmen perceived their jobs as more interesting and challenging because they now were working towards a goal of higher quality, rather than simply following standard procedures.

Taken together, the above discussion suggests that if operators are given the flexibility to achieve goals of improved efficiency, quality, or quantity in system output, active participation in system operations during both steady system states and emergencies will help operators reach these goals. The present study is designed to test this proposition directly. We experimentally manipulated the type of instruction crew members received. Operators were either told that they should learn the system's dynamics to prevent deviations and improve system efficiency (active participation) or that the system will set off an alarm when a system variable needs adjusting (passive participation). Two main effect hypotheses were tested concerning the effects of task participation on crew member detection performance during a steady system state, adjustment performance, problem-solving performance during a system failure.

1. When an automated system is in a steady state, crews who are actively participating with the system are expected to be better at preventing alarms and making adjustments when a problems arise compared to crews who are passively responding to system signals. Active participation in an automated system during a steady system state serves two purposes: (a) crew members should develop a more complete internal representation that they can, in turn, use to monitor the system and (b) crew members should feel more involved with the system, rather than being bored and distant, and therefore want to pay more attention to their system.
2. When an automated system fails crews who had been participating actively are expected to have more knowledge of the system and more

practice at a knowledge-based level of behavior. Therefore, they are expected to be more prepared to diagnose the failure compared to passive participants.

#### Communication between Crew Members

Lauber (1979) suggested that a large proportion of jet transport accidents, between the years of 1968 and 1976, involved a breakdown in crew communication. However, researchers are still uncertain about exactly which aspects of the communication process between operators facilitate performance and problem-solving. Given that emergency situations are typically rare and characterized by uncertain and novel circumstances, it is difficult to pinpoint what kind of communication process will be optimal.

Foushee and his coworkers (Foushee, 1981; Foushee, Lauber, Baetge, & Acomb, 1986; Foushee & Manos, 1981) completed a series of studies in an attempt to understand the group interaction processes involved in emergency and nonemergency situations. The conclusions reached were based on micro-communication analyses of transcript of interaction patterns between crewmembers in an aircraft and aircraft simulator.

The results of one study of communication patterns by Foushee and Manos (1981) suggests several coordination tactics that may improve crew performance. In addition to the effects of the quantity of information exchange, support was given for cross-checking, acknowledgement, and delegation. In other words, crews who exchanged more information about flight status; acknowledged commands, inquiries, and statements of observation by the other pilot; and properly delegated duties such that the most important tasks were performed first, made fewer overall errors. Another study by Foushee, et al. (1986) found that twin-jet transport crews who engaged in more task-related communication (versus non-task related communication) performed better. It was concluded that group coordination processes, in part, were responsible for performance differences. A micro-analysis of crew interaction supported the findings of Foushee and Manos (1981). Commands and acknowledgements were associated with better performance. In addition, higher performing group members (who were also those familiar with each other) made more suggestions and statements of intent. Overall, it seemed that these group members were more willing to exchange information. Crew members not familiar with each other spent more time on non task-related

communication as they tried to get to know each other.

Hackman and Kaplan (1974), in an attempt to isolate specific aspects of the group process that facilitates complex task performance, found that discussion of strategies is a facilitator when group member coordination is required. Observation of group processes showed that groups who discussed a strategy were more flexible in how they approached the task and better able to change task procedure when needed. Discussing strategies also led subjects to perceive that they had more influence over the outcomes of the task.

Finally, Bouton and Garth (1983) found that group processes and communication are a means of achieving active learning. They argue that groups engender a learning process that promotes the formulation of new ideas and the active construction of knowledge. By voicing ideas and information before it is understood, group members are able to create, discover, critique, and respond.

These findings suggest that communication is another means, in addition to actively pursuing goals, of actively participating in a system. If communication channels are open at all times, crew members can become familiar with each other and then proceed to exchange information and ideas while a system state is normal. Then, if an emergency arises, operators can make a smooth transition from monitoring behaviors to diagnostic behaviors when the rapid and timely exchange of information is essential.

In this study, communication was manipulated by telling operators to talk to each other constantly while monitoring the components of a system. They were told to talk about anything. Then, after crew members detected a system failure, they performed a diagnostic task to determine the cause of the failure. During the diagnostic task, communication was manipulated by encouraging operators to share information while problem-solving. Three additional hypotheses about the interactive effects of teammate communication and active versus passive participation were tested.

3. When the system is steady, crew members will be initially unfamiliar with each other and with the task. Therefore, communication is expected to slow detection of deviations in two ways. For active participants who are exchanging task relevant information while monitoring system variables, communication is expected to add to the complexity of the task. Yet these operators are expected to achieve their goal of system efficiency. For passive participants, communication is expected to increase the amount of time spent off the task. These operators are expected to talk more about task

irrelevant subjects and therefore, have the poorest monitoring task performance.

4. When the automated system fails, operators who had been most active while monitoring system components are expected to be most prepared to diagnose the cause of a system failure. It is expected that operators who actively participated with each other and with the system while monitoring will be most familiar with the current state of the system and will perform the best on the diagnostic task. Passive operators who spent time exchanging task irrelevant information rather than processing task relevant information while monitoring will be least prepared for an emergency. In addition, the timely exchange of information during the diagnostic task is expected to improve a teams performance.
5. Finally, post monitoring and post diagnostic task characteristic questions are expected to show that active participants are more prepared for emergencies than passive operators. It is assumed that active operators will perceive the characteristics of the monitoring task as similar to the characteristics of the diagnostic task if they used a knowledge-based type of behavior in both cases. Passive operators, on the other hand, are expected to perceive a great difference between the two tasks and consequently perceive the diagnostic task as more difficult and stressful. In an emergency, great increases in perceived workload and stress are undesirable.

## Method

### Subjects and Design

The operators used in this study were 112 undergraduate male students who participated as part of their introductory psychology course requirements. Each operator served as part of a 2-man team for one two-hour session.

A 2(monitors task communication) X 2(diagnosis task communication) X 2(task participation) X 2(task) split-plot design was employed. The two levels of communication while monitoring (communication vs no communication while monitoring subsystem components), communication while diagnosing (communication vs no communication while diagnosing a system failure), and task participation (active vs passive task instructions prior to monitoring) are between-subject factors. All crew members performed two tasks. First they monitored the components of a system, then, after the system failed, they diagnosed the cause of the failure.

### Tasks

Two context free tasks were used in this study: a monitoring task was used to study crew member monitoring, detection and adjustment behavior while the system was in a steady state and a diagnostic task was used to study problem-solving behavior among crew members during a system failure. Context free tasks were chosen so that no operator had an advantage over other operators because of prior knowledge of the system. The monitoring task consisted of two subsystems each containing 12-13 components requiring monitoring and some adjustments. In addition, the systems contained 6-8 shared components. These shared components did not have values to be monitored, rather, their values were monitored by the other crew member. The purpose of these shared components was to show each crew member in a team how components from the other subsystem affected the components they were monitoring. In addition, these components were included to encourage operators working together on the monitoring task to treat their subsystems as interdependent subsystems and thereby communicate, and share information about the subsystem. Operators not working together were able to look onto a screen next to them, displaying the other subsystem, to gather any information they needed to help them monitor their assigned subsystem. The subsystems are illustrated in Figures 1a and b.

The crew members' task was to monitor the two subsystems and keep component values within their assigned ranges. The subsystems contained both forward and backward causal flows. Appropriate ranges were assigned to components by following three rules: additive, subtractive, and exempt. These rules are listed in Table 1. The appropriate rule was chosen by examining the component's input and output causal relations with other components. When the values in the components were in their assigned range, the component was considered normal. Before a component deviated from normal, it reached a limit (3, 6, 9, 12, or 15). Limits were included to simulate conditions in which system variables were still inside an acceptable range, but adjustments were needed to prevent alarms or failures. If the limit was not detected and the component adjusted back to normal, the component value would exceed its normal range and an alarm (rectangular symbol) would appear in the component. The crew member's job was to make the appropriate adjustments and return component values back to normal as soon as an alarm was detected. If a crew member detected a limit, he

Figure 1a  
Subsystem A

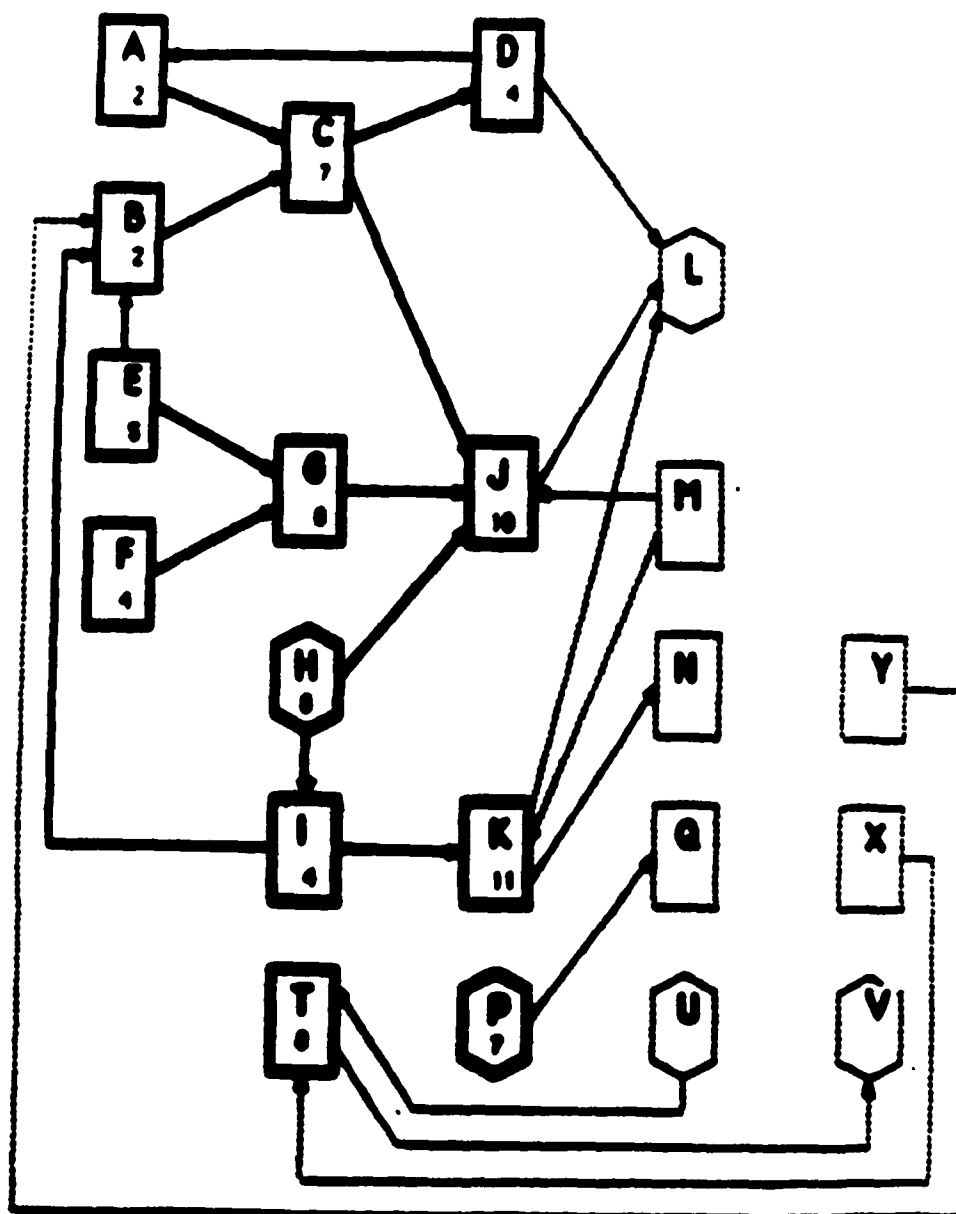
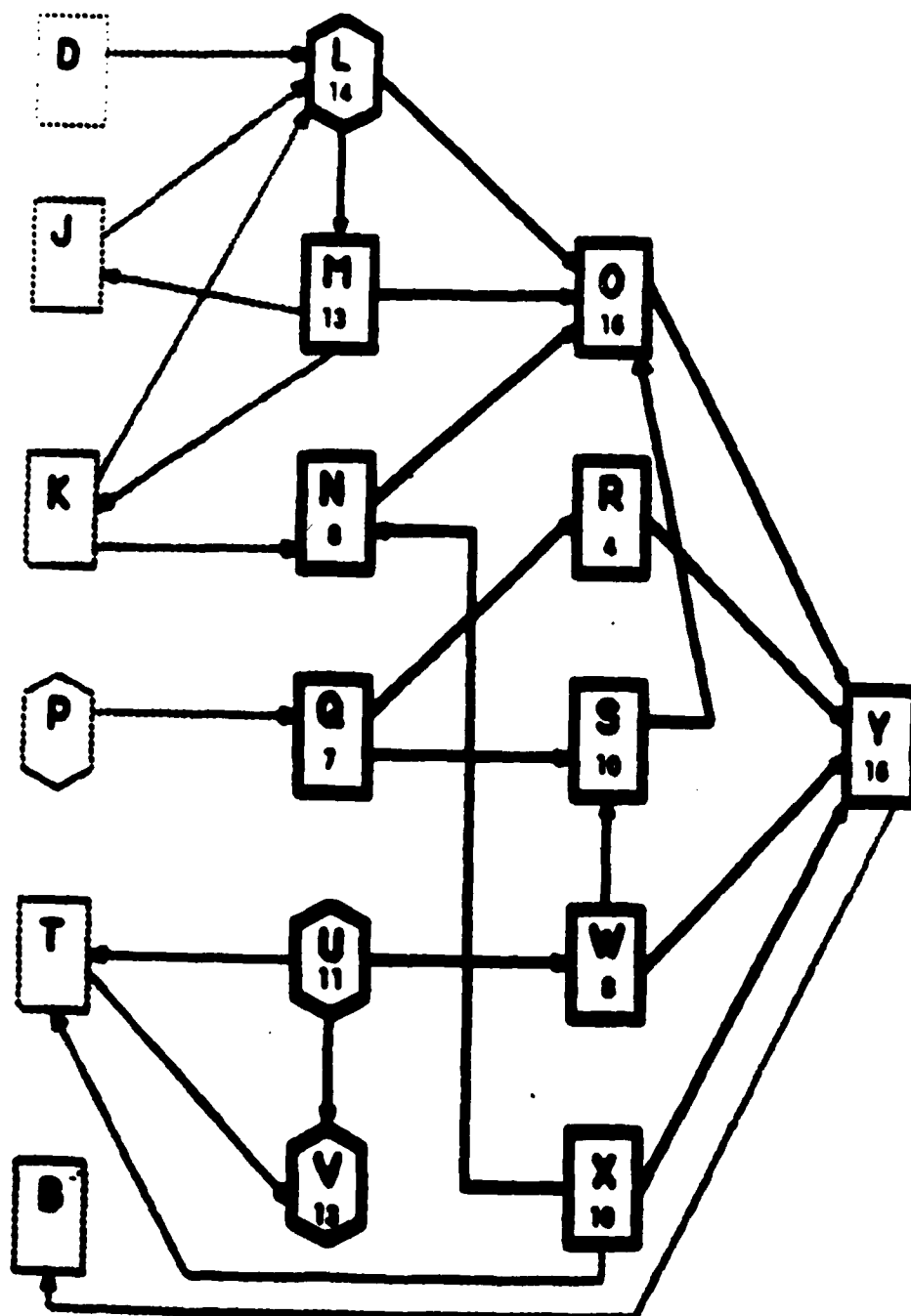


Figure 1b  
Subsystem B



was instructed to make the appropriate adjustment by using the arrow keys to increase or decrease the component values and return the component value back to normal before an alarm appeared.

Table 1  
Rules of Monitoring

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**ADDITIVE RULE**

When 2 components input into a third component, the level of both input components must be less than the third component.

**SUBTRACTIVE RULE**

When 1 component inputs into 2 other components, the value of the inputting component must be greater than at least one of the other 2 components.

**EXEMPTION RULE**

When a component has a value of '16', then it is exempt from the additive and subtractive rules. In other words, the rules do not have to be followed for this component. However, if the component deviates from 16 it must be adjusted.

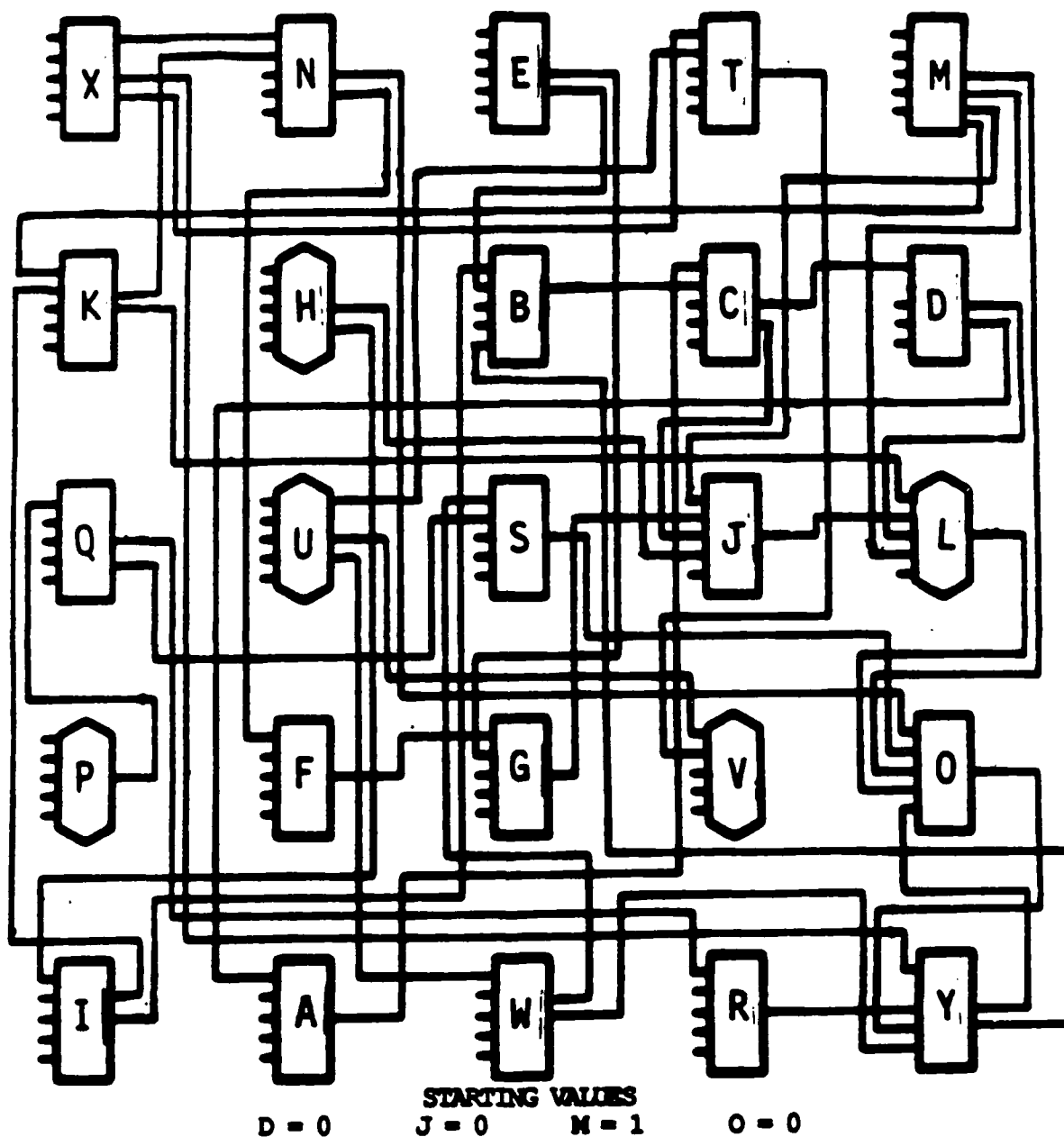
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Note: Several illustrations were provided with the rules.

The second task, a fault diagnostic task, was used to study crew member problem-solving behavior. Just prior to the diagnostic task, some components in the two subsystems were programmed to exceed their limits and fail to respond to crew member adjustment efforts. Detection of a system failure involved noting a difference between expected component levels following an adjustment and their actual levels. Once an operator detected the failure he began the diagnostic task. A modified version of Rouse's context-free task was used as the diagnostic task (see Rouse, 1979, for a description of the task and task rules). The Task is shown in Figure 2 along with the starting value screen that accompanied the network. Note, the network itself was presented to operators on paper. Only the starting values and an area for testing component links were presented on the computer. Starting values in this task provided crew members

Figure 2

Rouse's Diagnostic Task and Information Screen Presenting  
Starting Values and an Area for Link Testing



To test a link, type the name of the output component first, then the name of the input component. When you have determined the solution, press the F1 key.

	OUTPUT	INPUT	VALUE
1.	E	F	0
2.			

with information on the status of some components. This information was used to begin diagnosing the system failure. It was suggested that operators start at these components and work backwards to diagnose the source of the system failure.

The network presented in Figure 2 represents the same components and input to output relationships shown in Subsystems A and B. The combined subsystems make up 25 rectangular and hexagonal components. The fault diagnostic task represents the system after one failed component has caused numerous other components to fail because they received output from a bad or failed component. Operators saw some of these components go bad. That is how they knew the system had failed. To diagnose the failure, crew members started with information on the state of four components, worked backwards, and tested connections until a failed component was diagnosed.

#### Procedure

Operators were run in teams of two. Each operator was seated next to his teammate in front of an IBM PS-2 Model 30 micro-computer and received instructions orally while examples of system components and adjustment procedures were presented on the computer terminal. Operators were told that they were to be teammates monitoring components of a simulated system. Next they were provided task instructions involving an introduction to the system, component levels, and subsystem rules (see Table 1). All operators were given a few minutes to become familiar with the rules. Following the introduction, operators completed two practice trials to learn to detect limits, alarms, and make appropriate adjustments. A pilot study showed that the rules and adjustment procedures provided during these trials were simple enough for operators to learn the task in the time allotted. Finally, communication instructions were given to teams assigned to the monitoring task communication condition. This manipulation is described below.

The first 20-minute trial began by having teammates start their subsystem simultaneously while the experimenter started the audio equipment (tape recorder) and VCR. The VCR played a national geographic type film used to entertain operators becoming bored, feeling a loss of control, or finding their minds wandering. After 20 minutes, the monitoring task and film were stopped and operators were given a questionnaire that measured their knowledge of the

film and a questionnaire that assessed their perceptions of the task and its characteristics. In addition, operators were asked to draw the subsystem they had just monitored as one measure of their internal representation of the subsystem.

Following the questionnaire, the experimenter intervened with further instructions. Operators were told that they would complete a few more trials similar to the first trial. However, during these monitoring trials it was possible for the system to fail. They were told that a system failure occurs when one component quietly fails causing others to exceed their normal range. An operator would know that the system had failed when component deviations could not be adjusted. Once an operator detected a system failure they were told they would have to diagnose the cause of the failure. The diagnostic task was then introduced to operators and the operators were given practice subsystem pictures, similar although completely unrelated to the subsystems they were monitoring, and a practice problem-solving task. Operators were told to use the subsystem pictures to help them understand the relationship between system variables. It was much easier to figure out component interrelationships using subsystem pictures than using Rouse's network presentation. However, during the final diagnostic task, the only subsystem pictures operators were given were the picture they drew after the first trial. Thus, the more complete an operator's visual representation of their subsystem, the easier it was to trace the lines in the network. Operators were given 5 minutes to complete the practice diagnostic task. Half of the operators were told to communicate during the practice task and the other half of the operators were told not to talk to each other while problem-solving. A second monitoring trial began with the same subsystems as the first monitoring trial and the secondary task (the film). However, 8 minutes into the second trial, components failed to respond to adjustment efforts. Operators were given 2 minutes to detect the system failure and begin the diagnostic task. If the failure was not detected after 2 minutes, the monitoring task automatically ended. The secondary task terminated at the same time as the monitoring task. The diagnostic task began once operators called up the information screen on the computer and the experimenter distributed component networks (see Figure 2). Operators worked on the diagnostic task for up to 20 minutes. After operators entered a solution the

diagnostic task ended and operators were given a questionnaire that assessed their perceptions of the diagnostic task and its characteristics.

#### Independent Variables

Communication during the Monitoring Task. Prior to beginning the monitoring task, half of the teams were told that this was also a study of communication and therefore they should communicate continuously while performing the task. Operators were encouraged to ask questions, provide suggestions, describe what was happening on their subsystem, or if nothing was happening, to talk about the film playing on the VCR. During the first few minutes operators were prompted by the experimenter if they were not communicating.

Team members assigned to the no communication condition were told not to talk to each other while monitoring the subsystems and watching the film. In the event they needed information from the other subsystem, they were told to look over to a screen next to their own terminals displaying the other subsystem.

Active versus Passive Task Participation. Task instructions were used to get operators to actively or passively participate in the monitoring task. In the active condition, training was goal orientated and encouraged learning and task involvement. Operators were encouraged to use the additive and subtractive rules (properties of the system) to determine if components were at their normal levels. The instructions also stressed the fact that components would reach a limit before a component level exceeded its range and that their goal of maintaining system stability could best be met if they adjusted components before they deviated and set off an alarm. Finally, operators were told that in order to prevent alarms and make correct adjustments, they would have to pay close attention to component values and interrelationships.

Operators in the passive condition, on the other hand, were told that since they were monitoring an automated system the computer would follow the additive and subtractive rules to determine when components were deviating from their normal range. Training in this condition was response oriented. In other words, the instructions focussed on the stimuli from the system and how to respond to them. Little time was spend on instructing operators on the properties (rules) of the system or on how they could use the rules to keep the

system stable. Operators were told that a limit would appear before a component deviated and flashed an alarm but that they could adjust component levels when displaying limits or alarms. Finally, operators were reminded that the computer did set off alarms to signal deviations, therefore it was not necessary to watch the screen at all times.

Communication during the Diagnostic Task. Prior to the second trial, each operator assigned to the communication condition was told that both he and his teammate would have the same problem-solving task. Therefore, to increase their chances of good problem-solving performance they should talk to each other, share information, and coordinate their efforts. Operators were reminded that each teammate was familiar with half of the components and that they should use this knowledge to help each other solve the problem. It was suggested that each teammate start at a different place in the network, preferably with components they were familiar with, and that they share any information collected as well as the solution.

Operators in the no communication condition were also told that each teammate would have the same problem-solving task. Therefore, to increase their chances of good performance they should work independently. Operators were further encouraged to use their knowledge of half of the system to help them solve the problem.

#### Dependent Variables

The main dependent variable categories were operators' monitoring task performance, knowledge of their subsystem (internal representation), secondary task performance, and diagnostic task performance. Other dependent variables included the operators' responses to questionnaires following the monitoring task and then again following the diagnostic task. These questions assessed perceptions of task characteristics.

Performance on the Monitoring Task. Four measures of monitoring task performance were collected: (1) number of correct adjustments, (2) time to detect limits (maximum 10 seconds per limit), (3) time to detect alarms (maximum 20 seconds per alarm), and (4) adjustment time after detection (maximum 15 seconds per alarm). The computer was programmed to collect the data on each of these variables.

Accuracy of Operator Internal Representation. A visual representation or mental image of the system was used as a measure of an operator's internal representation. The mental image was assessed by having operators draw the subsystem they monitored. Three measures of mental image accuracy were computed: (1) number of correct components and component letters, (2) number of correct links, and (3) number of correct component values. In addition, these three scores were added to compute a total mental image score.

Secondary Task Performance. A film was shown during the monitoring task to provide operators with something to do other than the task. Twenty-one open-ended questions were used to measure the operators familiarity with the film. Operators earned two points for each correct response, one point if they remembered the scene but could not remember the answer or if they answered incorrectly, and zero points if they could not respond. The scores for each question were totaled and used as a measure of the extent operators' focus of attention was on the film rather than on the monitoring task.

Performance on the Diagnostic Task. Two measures of diagnostic task performance were collected. The first measure was the time it took operators to enter a solution to the diagnostic task. Secondly, measures of the accuracy and plausibility of the final solution were collected. All operators received either a score of 0 for an incorrect solution or a score of 1 for a correct solution. In addition, when the data were available, the incorrect solutions were rank-ordered according to the plausibility of the solution. The rules developed by Rouse, Rouse, and Pellegrino (1980) for evaluating maintenance performance on the problem-solving task were used to evaluate the operators solutions in this study. Low values were given to starting value components or components connected to the starting values because the status of these components should have been obvious (i.e. components M and A; see Figure 2). Components receiving no inputs and sending good or normal outputs were next in the rank ordering (i.e. components E and H). Components receiving multiple bad inputs and sending bad outputs were placed in the middle of the rank ordering (i.e. components C and L). In these cases operators had multiple opportunities to determine that some other component was causing these components to fail. Finally, those components receiving both good and bad inputs and sending bad outputs were placed high in the rank ordering (i.e. components B, N, & G). Here

operators fell into the trap of concluding that the component was the cause of the failure just because one of its inputs had not failed. In most cases, testing the other input links would have led them to the correct solution, X. Thus, the dichotomous scoring of 1 = correct solution and 0 = incorrect solution was replaced by the following rank order of possible solutions: 10 = X (highest rank), 9 = B, 7.5 = N & G, 6 = L, 5 = C, 3.5 = E & H, 2 = A, and 1 = M (lowest rank).

### Communication Analyses

Inter-operator communications were tape recorded and later analyzed in a procedure similar to that used by Foushee and Manos (1981) and Foushee et al. (1986). Consistent with this approach, each statement in the communication transcript was coded into one of the following 17 categories of communication: error, comment, non-task related, operator role, observation, inquiry, response to inquiry, volunteer information, repeat, acknowledgement, confirm/cross-check, disagreement, tactical statement, command, suggestion, review/overview, and uncertainty. Two additional categories were created as subsets of the Inquiry and Voluntary categories--reactive and proactive. Reactive statements were those directly related to the subsystem on the screen whereas proactive statements involved information integrating the two subsystems and subsystem components. These categories are listed in Table 2.

To facilitate analyses, improve the distribution of the communication variables, and increase the reliability of the analyses, highly correlated categories and categories with low frequencies were combined. Those categories with extremely low frequencies were dropped. The eight categories used in the analyses are as follows:

- (1) Confusion = Comment + Uncertainty + Error
- (2) Task Irrelevant = Non-Task Related + Role
- (3) Reactive Inquiry
- (4) Proactive Inquiry
- (5) Reactive Volunteer = Volunteer (Reactive) + Observation
- (6) Proactive Volunteer = Volunteer (Proactive) + Suggestion + Review  
+ Disagree
- (7) Acknowledgement = Acknowledge + Confirm/Cross-Check
- (8) Tactical

Table 2  
Inter-Operator Communication Categories

Category	Definition
Error	A statement recognizing or apologizing for an incorrect response. e.g. "Oh, I didn't want to press ENTER."
Comment	A non-informative statement about the task or experiment. e.g. "Looking at all this at once is difficult."
Non-Task Related	Any statement and response not related to the present task. e.g. "Wow, look at that man and the ostrich."
Operator Role	Statements defining the role of the operators. e.g. "There's not much to do except watch the screen."
Observation	Statements relaying factual information or conveying information redundant with subsystem displays. e.g. "I've got a whole bunch of numbers at different values."
Inquiry	Request for task related information.  a) <u>Reactive</u> . Request for information on component values, tactical information, deviations, and in the diagnosis task, information on the status of links. e.g. "What's the value of 'M'?"  b) <u>Proactive</u> . Request for information on the other subsystem and on relationships between subsystem components. e.g. "What is 'M' connected to?"  c) Questions about the task e.g. "What are these empty components for?"  d) Questions about the rules or procedures. e.g. "Are we suppose to fix it when it's a limit?"
Response to Inquiry	Statement in response to the other operator's inquiry beyond acknowledgement. Responses fall under the same subcategories as Inquiry (a - d).
Volunteer Information	Task-related information conveyed without a request.  a) <u>Reactive</u> . Volunteering information on component values, deviations, or in the diagnosis task, information on the status of a link. e.g. "N just deviated."

Table 2 continued

	<p>b) <u>Proactive</u>. Volunteering information on component relationships, subsystem dynamics, and in the diagnosis tasks, conclusions about the status of components based on tested and untested link information. e.g. "J's connected to your M which connects to your O and then your Y."</p> <p>c) Volunteering information about the task. e.g. "A bar will appear above a component when it deviates."</p> <p>d) In the diagnosis task, suggesting a solution to the task. e.g. "I think the solution is 'X'."</p>
Repeat	Restatement of previously stated information.
Acknowledge	A nonevaluative statement or phrase letting the other operator know his information was heard. e.g. "Alright."
Confirm/ Cross-Check	Statements verifying or corroborating information. e.g. "Your right, the H to J link is normal."
Disagreement	Failure to concur with the other operator. e.g. "I don't think E goes to C."
Tactical Statement	Statements conveying information about an intended action or discussion of an appropriate action. e.g. "I've got to watch 'E'."
Command	Communication in which a request for a specific act is issued. e.g. "Go back and work on this section."
Suggestion	Communication in which a specific action is suggested. e.g. "How about testing E to B."
Review/ Overview	A survey or summary of acquired task-related information. e.g. "OK we know the P to Q link is normal."
Uncertainty	Statements indicating a lack of information with which to respond or perform. e.g. "I don't understand this."

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## Results

### Monitoring Task

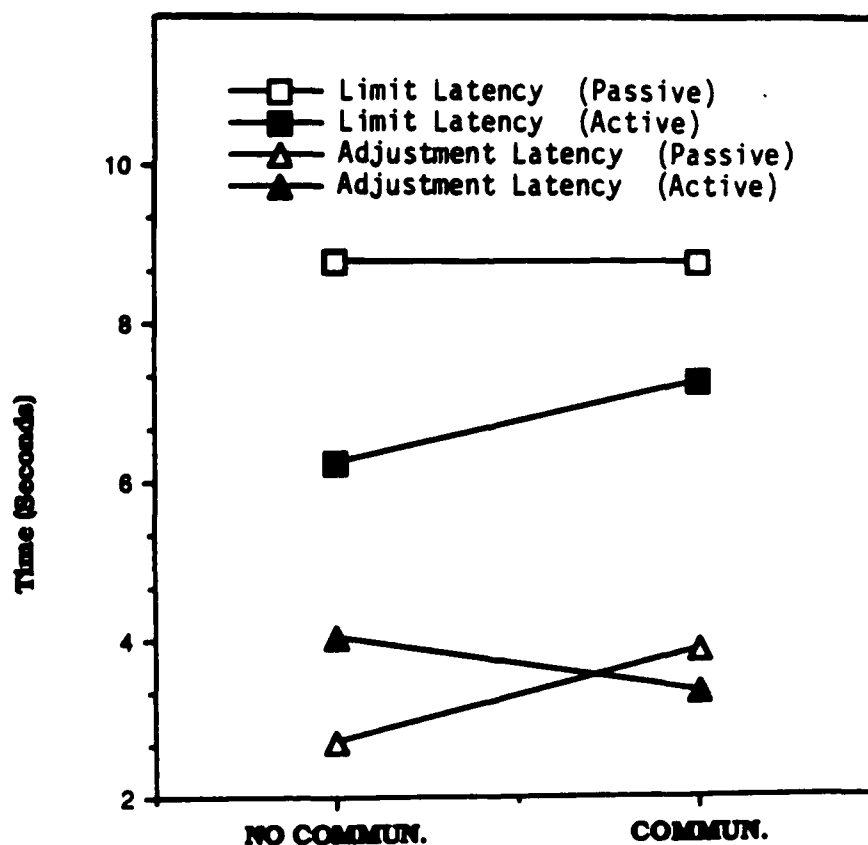
Task Performance. Monitoring task performance, in this study, was evaluated by an operator's ability to detect limits and alarms quickly, and by his ability to quickly and accurately respond to deviations. Consistent with the first hypothesis, active operators were better monitors than passive operators. Analysis of variance resulted in a significant main effect of task participation on the amount of time operators took to detect limits, (6.7 seconds for active operators vs 8.8 seconds for passive operators,  $F(1,89) = 41.11$ ,  $p < .001$ ); and for the amount of time operators took to detect alarms, (3.1 seconds for active operators vs 4.8 seconds for passive operators,  $F(1,88) = 6.92$ ,  $p < .01$ ). As expected, operators actively participating with the system engaged in knowledge-based behavior intended to help develop their information processing skills in addition to giving them information on how to respond to the task. This behavior allowed them to pay more attention to the task and their goal of keeping the system stable.

This finding was strongly supported by analyses of post-task film question scores and partially supported by analyses of mental image scores. The post-task film questions were designed to assess an operator's knowledge of the information presented in the film. It was assumed that to the extent operators were paying attention to the film they could not be monitoring their subsystem. Analysis of variance on the operators' total film scores showed that active operators knew much less about what went on in the film (mean score of 11.9) compared to passive operators (mean score of 24.6),  $F(1,106) = 69.55$ ,  $p < .0001$ . In addition, operators were asked to rate (1) how much they watched the film and (2) the extent to which they would be able to describe what went on in the film. Operators who were passive participants reported that they watched the film significantly more than active participants ( $M = 4.2$  vs  $2.5$ , 7-point scale),  $F(1,106) = 51.55$ ,  $p < .0001$ ; and that they were more able to describe the film ( $M = 4.1$  vs  $2.9$ , 7-point scale),  $F(1,106) = 25.85$ ,  $p < .0001$ .

Analyses of mental image scores provided only weak support for the superiority of active participation over passive. Analysis of variance on the mental image scores revealed only a marginally significant difference between active versus passive operators' knowledge of the correct component levels,

$F(1,109) = 3.40, p < .07$ . Active operators knew an average of 1 more component value than passive operators. It seems strange that the operators' visual representation of their subsystem did not differ much when there were significant differences in their performance and film scores. Perhaps a visual representation of the operators' internal model was inappropriate for evaluating system control and monitoring behavior. Landeweerd (1979) found that a visual-spatial image of a process is appropriate for diagnostic performance, and verbal descriptions of what causes what are more appropriate for an accurate description of an operator's performance as a controller. Therefore, analyses of the communication data presented below may provide much more information about an operator's development of accurate and complete system knowledge.

Figure 3  
Task Participation by Monitoring Task Communication Interactions for  
Limit Detection and Adjustment Latency



In the third hypothesis it was proposed that communication would add a degree of complexity to the task and consequently slow down operator detection performance. As expected, inter-operator communication did slow down the operator's alarm detection times,  $F(1,89) = 7.65, p < .01$ . In addition, marginally significant communication by task participation interactions resulted for both latency of limit detection,  $F(1,89) = 3.65, p = .06$ ; and latency of adjustments,  $F(1,89) = 3.24, p = .08$ . These interactions are illustrated in Figure 3. As shown by the two lines at the top of Figure 3, communication had no effect on the latency of limit detection for passive operators, however, it was found to slow the detection rate of active operators by an average of 1.1 seconds. Communication had a different effect on adjustment latency. Communicating information about subsystem components helped actively trained operator make faster adjustments. Although weak, this finding provides partial support for the hypothesis that communication helps operators share information needed to actively interface with the system.

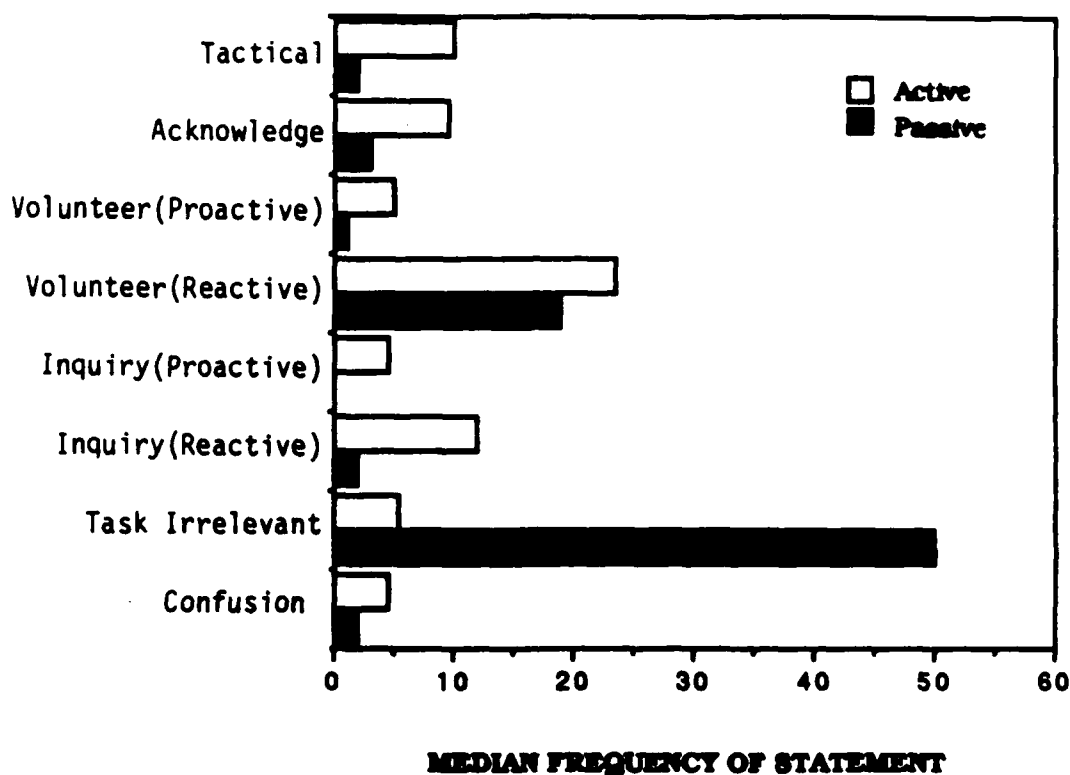
Analysis of total film scores also provided some evidence that communication increased the operators active involvement in the system. Communicating operators knew significantly less about the film compared to noncommunicating operators ( $M = 15.9$  vs  $19.6$ ),  $F(1,106) = 5.44, p < .05$ . Of course, there is no data to show that communicating operators, who were not watching the film, were instead monitoring their subsystem.

Communication while monitoring did not, however, help improve the operator's mental images of the system. Communicating operators remembered significantly fewer component levels compared to noncommunicating operators,  $F(1,109) = 11.07, p < .001$ .

Communication During the Monitoring Task. Multivariate analyses and frequencies were used to examine the effects of passive vs active task participation on communication. Figure 4 presents a bar graph plotting the median frequencies of each statement for passive and active teams who communicated while monitoring. One of the most noticeable differences between the two groups was in the total number of statements communicated. Passive teams communicated an average of 20.5 statements less than active teams ( $96.2$  vs  $116.5$ ), respectively. In addition, given that many of the statements communicated in the passive condition were task irrelevant, passive

participation was related to a significant reduction in the amount of task related information communicated (50 statements for passive teams versus 106 statement for active teams).

Figure 4  
Monitoring Task Communication Patterns



According to the figure, other noticeable differences include more inquiries (both proactive and reactive), volunteer statements (both proactive and reactive), acknowledgements, and tactical statements communicated by active teams compared to passive teams.

Discriminant analysis (Cooley & Lohnes, 1971; Klecka, 1980) was used to explain the differences between the passive and active teams with respect to the communication category variables. The resulting standardized coefficients suggested that the communication categories of task irrelevant statements and acknowledgments contributed most to the discriminant scores. The resulting

function could be referred to as a 'pro-information' function. The resulting Wilks' Lambda was .30,  $\chi^2(8) = 28.04$ ,  $p < .001$ , and the canonical correlation between the groups and the discriminant function was .84.

#### Diagnostic Task

Task Performance. Diagnostic performance, in this study, was evaluated by the plausibility of the solution entered and the time it took operators to enter a solution. Contrary to our predictions, however, communication while monitoring did not have a significant effect on the correctness or plausibility of the solution. In fact, this behavior was found to slow down diagnostic time significantly for passive operators. This effect was seen in the analysis of variance on total time to diagnose the failure that resulted in a marginally significant monitoring communication main effect,  $F(1,76) = 3.60$ ,  $p = .06$ ; and a significant monitoring communication by task participation interaction,  $F(1,76) = 4.83$ ,  $p < .05$ . Figure 5 illustrates the slowing effect of monitoring communication on the time it took for passive operators to diagnose the failure.

Figure 5

Task Participation by Monitoring Task Communication Interaction for Failure Diagnosis Time

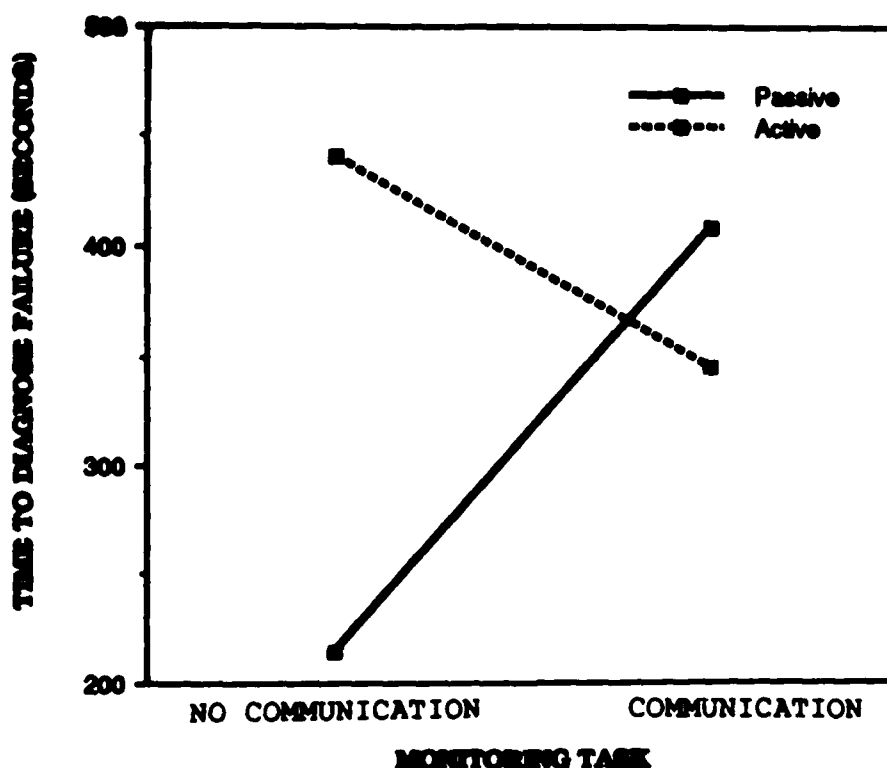
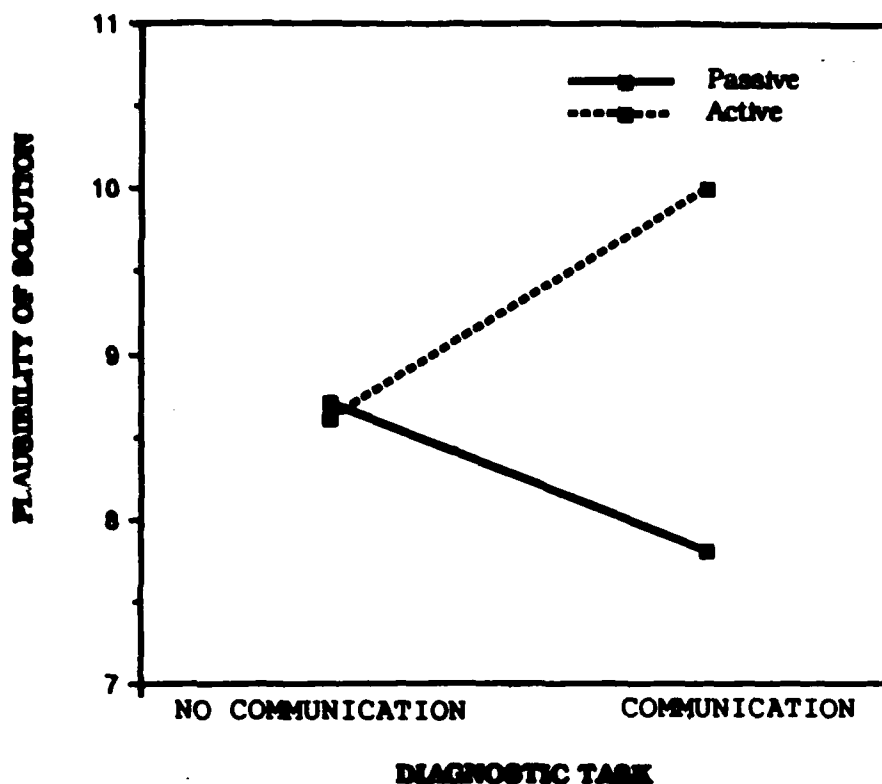


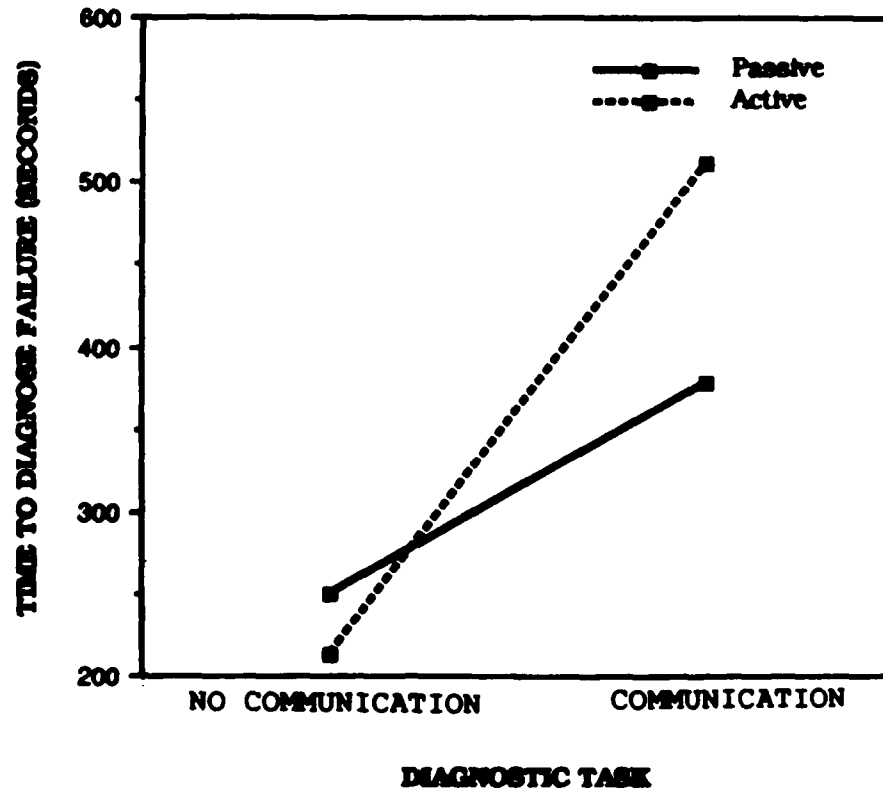
Figure 6  
Task Participation by Diagnostic Task Communication Interaction  
for Plausibility of solution



Partial support was found for the hypothesized beneficial effects of communication and active participation on diagnostic performance. Analysis of variance on the plausibility of the solution resulted in a marginally significant diagnostic communication by task participation interaction,  $F(1,25) = 3.20$ ,  $p=.08$ . This interaction is illustrated in Figure 6. As expected, active operators who communicated while problem-solving entered the most plausible solutions whereas passive operators who communicated while problem-solving entered in the least plausible solutions. Figure 7 shows that communicating while diagnosing increased diagnostic time for both active and passive operators,  $F(1,76) = 3.94$ ,  $p<.05$ . Active operators who communicated while problem-solving took the longest to diagnose the failure, however, these operators entered the most plausible solution. This is a classic illustration

of a speed-accuracy tradeoff. Thus, it appears that the benefits of taking extra time to collect, process, and analyze information outweigh the costs (a few seconds).

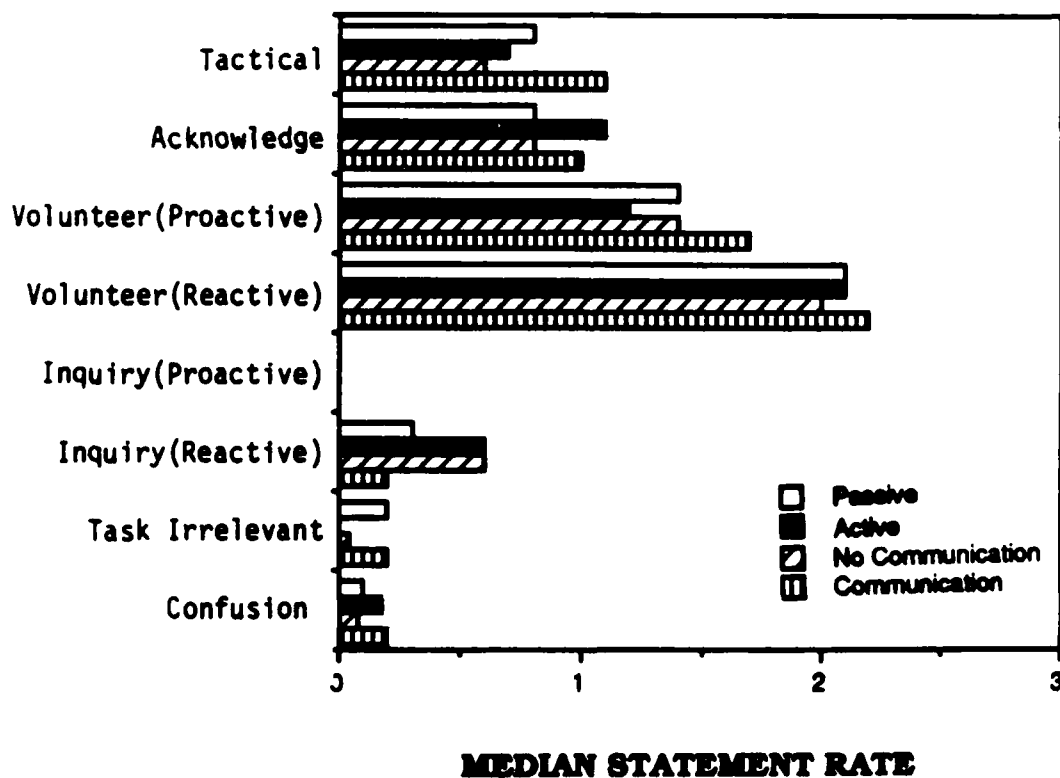
Figure 7  
Task Participation by Diagnostic Task Communication Interaction  
for Failure Diagnosis Time



Communication During the Diagnostic Task. Discriminant analyses and rate of communication statements were used to examine the effects of passive versus active participation and communication while monitoring on diagnostic communication patterns. Figure 8 presents a bar graph plotting the rate of each statement for teams who passively versus actively participated and for teams who communicated versus those who did not communicate while monitoring. Clearly, data from the teams who communicated while diagnosing the failure could be used in this analysis. As the figure illustrates, the communication patterns for the four groups are very similar to each other and not as similar to the monitoring

task communication patterns. Discriminant function analyses on the diagnosis communication categories used to discriminate between active and passive operators and between operators who communicated while monitoring and operators who did not communicate while monitoring resulted in nonsignificant functions,  $p > .25$ . Thus, it appears that communication patterns are task specific. A comparison of the patterns illustrated in Figures 4 and 8 shows a substantial increase in the number of statements exchanged in the tactical, acknowledgement, and volunteer categories and a substantial decrease in the task irrelevant category. This difference is more pronounced for passive operators. Although the patterns within a task are more similar than between tasks, the results of the performance data presented above show that communicating while monitoring did effect performance on later diagnostic tasks.

Figure 8  
Diagnostic Task Communication Patterns



### Perception of Task Characteristics

Thirty-six post-task questions were written to assess perceived characteristics of the monitoring and diagnostic tasks. Confirmatory factor analysis was used to reduce the 36 task perception items to the following seven task characteristics: (1) judgement--the amount of decision making required by the task; (2) task difficulty; (3) motivation required by the task; (4) responsibility or influence over outcomes of the task; (5) communication requirements--requirements to work with others and coordinate activities; (6) skill variety--requirements for the use of several skills or the performance of different kinds of tasks; (7) level of knowledge--information gathering requirements. These characteristics were judged to be the most relevant for tasks in automated systems. Three to five items were written for each task characteristic category. The questions were distributed to operators following the monitoring task and once again following the diagnostic task. Both data sets were factor analyzed using the confirmatory factor analytic procedure available in LISREL VI (Joreskog & Sorbom, 1984). The resulting factor pattern showed that the task perception items assessed the expected task characteristics. The overall  $\chi^2$  goodness-of-fit statistic for the monitoring task items was 545 with 300 degrees of freedom. For the diagnostic task items, the resulting  $\chi^2$  statistic was 607 with 300 degrees of freedom. The items associated with each factor were then summed together and the judgment, task difficulty, motivation, responsibility, communication, skill variety, and level of knowledge task characteristic categories were used throughout the analyses.

Monitoring Task. Discriminant function analysis was used to study the differences between active and passive operators with respect to the seven task characteristic categories. The discriminant analysis results suggest that the task characteristics of level of motivation and perceptions of task difficulty differentiate the two task participation groups. The resulting Wilks' Lambda was .69,  $\chi^2(7) = 39.87$ ,  $p < .0001$ , with a canonical correlation of .45. Active operators perceived greater requirements for determination, persistence, effort, and motivation, and consequently reported that the task was more difficult and required more attention compared to passive operators.

These results suggest that active involvement in the monitoring task increases an operator's workload and perceptions of task difficulty. If the

monitoring task is routine and requires little human intervention, encouraging an active task orientation that increases operator responsibility and system intervention may prevent boredom and inattentiveness.

Discriminant analysis used to discriminate between communicating and noncommunicating groups resulted in a nonsignificant function,  $p=.19$ .

Diagnostic Task. Discriminant analysis was also used to examine the extent to which the seven task characteristic categories (based on data collected after the diagnostic task) are able to discriminate between task participation and communication groups. Initial discriminant analyses showed that operators who communicated while monitoring and operators who did not communicate while monitoring did not differ on these diagnostic task characteristic variables. Therefore, one discriminant analysis was completed on the following four groups: (1) passive operators who communicated during the diagnostic task; (2) passive operators who did not communicate during the diagnostic task; (3) active operators who communicated during the diagnostic task; and (4) active operators who did not communicate during the diagnostic task. Only the first function was significant at the .05 level. This function received high loadings from the communication task characteristic and appears to discriminate between operators who communicated while diagnosing and those who did not communicate while diagnosing. The Wilks' Lambda for this function is .59,  $\chi^2(21) = 56.33$ ,  $p<.0001$ , and the resulting canonical correlation is .55. Operators communicating while diagnosing the cause of a system failure perceived that multiple operators were needed to complete the task, more than noncommunicating operators. In addition, communicating operators responded higher than noncommunicating operators to questions about how helpful communication and coordination was (would be) to diagnostic performance.

A second function was significant at the .10 level and showed the highest loading for the judgment variable, and so will be referred to as a judgment function. According to the canonical discriminant functions, perceptions of judgment requirements differentiate the task participation groups. Consistent with the fifth hypothesis, operators who participated passively perceived the diagnostic task as more demanding than operators actively participating. Passiveness resulted in operators who perceived that they had to use more judgment when performing the diagnostic task, that the diagnostic task was less

cut and dried, and that they had to make more different kinds of responses at the same time, compared to active operators.

Additional questions not included in the discriminant function analysis were analyzed separately. ANOVA resulted in a diagnostic task communication main effect for the perceived importance of knowledge of both subsystems,  $F(1,104)=9.05$ ,  $p<.01$ , and for the extent operators felt they knew the subsystems,  $F(1,104)=6.74$ ,  $p<.05$ . In both cases, the responses of communicating operators were higher than for noncommunicating operators. In addition, these items also produced some interesting interactions. ANOVA resulted in a significant monitoring communication by diagnosis communication interactions for the extent to which operators perceived the diagnostic task as stressful,  $F(1,104)=6.13$ ,  $p<.05$ ; and as a task that requires close monitoring prior to failure,  $F(1,104)=3.47$ ,  $p=.06$ . Responses to these post-task items suggest that operators who made a transition from not communicating while monitoring to communicating during the diagnostic task perceived the diagnostic task as most stressful and demanding, and operators who communicating while monitoring and continued to communicate during the diagnostic task perceived the task as least stressful and demanding. Thus, communicating while monitoring may have helped operators make the transition from the monitoring task to the diagnostic task if they were allowed to continue to communicate.

Shifts in Task Perceptions. It was hypothesized that the diagnostic task would be perceived as motivating, challenging, and difficult, compared to a routine monitoring task. To test for a shift in task perceptions from the monitoring to the diagnostic task, Student T-Tests were computed on the difference scores for each task characteristic category. Table 3 shows significant mean difference for all the task characteristics. As expected the diagnosis task was perceived to require more cognitive skills, responsibility, effort, skill variety, coordination, and task difficulty. It is unclear from these analyses, however, whether the perceptual differences were a function of objectively different task characteristics or if they were influenced by operator task participation and communication manipulations. According to the fifth hypothesis, the difference scores should be much greater for passive operators than for active operators. Passive operators were expected to perceive the monitoring task as low on all task characteristics. Therefore, by

contrast, the diagnostic task was expected to be perceived as very different and much higher on all task characteristics for passive operators compared to active operators.

Table 3  
Means and T-Test Results for Post-Task Questions

Post-Task Questions	Monitoring Task	Diagnosis Task	T Value	p
	Mean	Mean		
Judgement	3.64	4.48	-6.18	.000
Task Difficulty	3.37	4.92	-9.77	.000
Motivation	4.69	5.39	-4.66	.000
Responsibility	4.16	4.44	-2.32	.022
Communication	4.09	4.71	-3.98	.000
Skill Variety	3.31	3.96	-5.83	.000
Level of Knowledge	3.14	4.87	-12.33	.000

N = 113.

To examine if the task participation and communication groups can be differentiated by task perception differences, discriminant analysis was used on the difference scores between the diagnosis and monitoring task characteristic responses for each of the seven task characteristics. Once again, attempts to discriminate between operators who communicated and operators who did not communicate while monitoring were unsuccessful, therefore, the monitoring task communication variable was not included in the final analysis. The four groups used in the analysis were (1) passive operators who communicated while diagnosing; (2) passive operators who did not communicate while diagnosing; (3) active operators who communicated while diagnosing; and (4) active operators who

did not communicate while diagnosing. Two functions were found to significantly discriminate between these groups. The first function, receiving high loadings from task difficulty and motivation, differentiates between the active and passive operators. The resulting Wilks' Lambda for this function was .48,  $\chi^2(21) = 77.82$ ,  $p < .0001$ , with a canonical correlation of .59. As hypothesized, the increase in effort, persistence, determination, attention, motivation and mental capabilities required by the diagnostic task compared to the monitoring task, were much greater for the passive operators than for the active operators.

The second function had a high positive loading from the communication task characteristic and a moderately sized negative loading from the responsibility task characteristic. This function differentiates between operators who communicated while diagnosing and operators who did not communicate while diagnosing. The resulting Wilks' Lambda for this function was .73,  $\chi^2(12) = 32.80$ ,  $p < .001$ , with a canonical correlation of .51. This function reflects a change in attitude towards the importance of communication and cooperation. During the monitoring task, operators did not perceive communication and coordination as very important. However, operators not allowed to communicate while problem-solving, greatly increased their ratings of the importance of communication and coordination compared to operators told to communicate while problem-solving. It appears that operators not allowed to communicate felt the diagnostic problem would be easier to solve if they could share information with their teammates. On the other hand, communicating operators perceived the problem-solving task as requiring less responsibility compared to noncommunicating operators; they shared the responsibility with their teammate. This diffusion of responsibility was related to a reduction in perceived stress and workload by communicating operators. However, it was only related to a reduction in diagnostic performance for passive operators.

### Discussion

Recently researchers have suggested that by creating an active work environment that encourages operators to seek information (Schuck, 1985); use their judgment skills (Brecke, 1981); explore a system's potential (Carroll et al. 1985); and use knowledge-based behavior rather than rule-based behavior (Rasmussen, 1983), they will be better able to control an automated system and

handle unplanned changes. Wiener (1985), with particular interest in pilots of aircrafts, made a plea to researchers and designers to

"reexamine the role of the monitor, to discover a way to make the monitoring task less passive and more interactive with the machines, and to keep the operator in the loop..." (pg. 88).

Wiener and Curry (1980) suggested that operators of aircrafts should be allowed more freedom to make decisions on desired control actions. In order to provide more opportunity for judgment and active participation, Brecke (1981) advocated changing our instructional programs.

Although the study presented in this paper was not a study of training procedures, active participation was manipulated through task instructions. As predicted, instructing operators to actively acquire, process, and use information from a system to achieve operation and output goals resulted in better performance on the monitoring task. More importantly perhaps, when coupled with communication, active participation also helped operators handle stressful emergency situation.

These findings demonstrate that automated technology is not deterministic; it is not unconditionally responsible for the distance that usually exists between operators and a system. Rather, designers of operator-machine systems, task instructional programs, and work environments must decide what role the human should play when monitoring a highly automated system. Based on the results of this study, an active role seems most appropriate.

Active participation was used, in this paper, as a generic term to describe behaviors that are "less passive and more interactive with the machine" (Wiener, 1985). The development of active participatory behaviors begins with the structuring of knowledge that can be used to guide scanning actions, form expectancies, make inquiries, and produce control actions that are consistent with an operator's goal state (internal representation). In this study, active participation resulted in slightly more accurate knowledge of the system which, when combined with increased information processing activities, resulted in better monitoring performance. Consequently, active operators were less bored and perceived higher workload when they were actively involved compared to passive participants.

In addition, active participants were better able to problem-solve when the system failed. Much of their superior performance in these situations may

be attributable to active information gathering and information processing activities performed while the system was in a steady state. By having more information and more practiced information-processing skills, active operators experienced less stress and workload when diagnosing a system failure compared to passive participants. In other words, the increased workload operators experienced while actively monitoring helped active operators develop the skills they needed to handle emergencies.

A second variable of interest in this study was communication. Communication between teammates is not a new variable. In fact, hundreds of studies of group performance and communication can be found in the social psychology literature. The reason for the renewed interest in communication is because, through the introduction of new technology, group members are controlling different, more complex, systems such that the consequences of breakdowns in communication and coordination are very costly and may even be fatal. Rather than working on one task or system as a group, each operator often has information on only one subsystem of a complex system. When the system is normal, the subsystems may often be treated as relatively independent components. However, once the system is in an abnormal state, the disturbance could affect many subsystems. Now the subsystems are viewed as interdependent. While a crew is problem-solving, communication is used for organization and delegation, information, and validating and cross-checking information.

One question addressed in this paper concerns the purpose of communication prior to an emergency. Foushee et al (1986) found that communication increases crew members' familiarity with each other and consequently helps operators understand when and how to share information in a timely manner. Bouton and Garth (1983) suggest that communication in a group increases active learning. The results of the present study show that communication while monitoring was not beneficial to performance during the monitoring task nor during the diagnostic task. Communication among crew members did not lead to improved adjustment performance and, in fact, resulted in slower limit and alarm detection times. However, according to McGrath (1984), communication acts serve to transfer both task relevant and interpersonal messages. In continuing work groups, such as crews of highly automated systems, operators require a stable pattern of interpersonal relations. Perhaps verbal exchanges early in the task

help develop these relations. In addition, with the proper task indoctrination, communication can serve as a channel for communicating task relevant information. Analysis of monitoring task communication patterns show that communication combined with active participation increased the frequency of task relevant statements volunteered, the number of inquiries, and the frequency of cross-checking and acknowledgements; all types of statements that are desired in communication between crew members (see Foushee et al., 1986). In addition, the interaction between communication and task participation on the time it took operators to make adjustments suggests that the degree of operator involvement in a monitoring task may moderate the benefits of communication. It was found that communication helped operators make faster adjustments when they were actively participating in the system but slowed down adjustment time for passive operators.

Stronger support was found for the benefits of communication while problem-solving. Active operators who communicated while diagnosing the system failure entered the most plausible solutions to the problem. Part of their success can be attributed to the timely exchange of information during the emergency. This lends support to the notion that communication skills are important for all operators confronted with anomalies, breakdowns, or failures.

This study has implications for designers of complex systems and training programs. If active participation is desired in highly automated systems, system designers must allow operators a means to integrate information and use the information to reach a desired goal state. Active human-machine interfacing can be assisted by providing operators with simulations of the system to view the consequences of their adjustments prior to resetting parameters on a real system; predictive displays to facilitate prediction and judgments; or historical displays to provide trend data from which operators can extrapolate to the future. In addition, interactive simulations and networked computer systems may help operators become familiar with each other's knowledge structures and consequently communicate information in a timely manner.

The results of this study also suggest a move away from rule and procedure based training and a move towards a cognitive approach. Operators must be trained to realize that there are a lot of uncertainties in complex automated systems and that information processing, communication, and judgment skills are

important. Also, operators must learn to set goals of improving system efficiency, increasing productivity, or maintaining stability. In turn, they will begin to realize the importance of their responsibilities to the system and to other operators.

Based on the above discussion, an active operator role appears to be more than prescribed behaviors. It is a pedagogy that can be incorporated into a work environment through training, system design, and management. As more research is completed on the role of operators, an interactive theory combining the groups literature, models of automated processes, and research on human-machine interaction, can be developed that bridge the gap between engineers, designers, trainers, psychologists, management, and workers.

The present study was an integration of these three areas, however, it is clear that we are limited in the generalizations that can be made given that this was only a lab study; real complex systems may differ significantly from context-free systems. The operators in this study only worked on the monitoring task for an hour rather than days or even years. Also, the context free nature of the task made it difficult for operators to acquire a large knowledge base common among operators of real systems, and to communicate relevant information in a timely manner. These two aspects of our experimental procedure made it difficult to study the development of operator knowledge structures. On the other hand, the communication results from this study are consistent with past studies (Foushee & Manos, 1981) and results from the task participation variable are consistent with predictions in the education and aviation psychology literature. Thus, communication and active human-system interactions appear to be important aspects of the new role of human operators that deserve further consideration.

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